Predicting Weather at RDU
using Time Series Modeling

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Agenda

01 Data

02 Data Analysis

03 Feature Engineering

04 Linear Regression

05 Random Forest

06 Model Performance

Data

Hourly Temperature from RDU

- Hourly weather data from RDU Airport
    - Meteostat’s bulk data
- Temperature, Humidity, Precipitation, etc.
- Only kept temperature and year-month-day-hour -> Datetime index

Data from past years

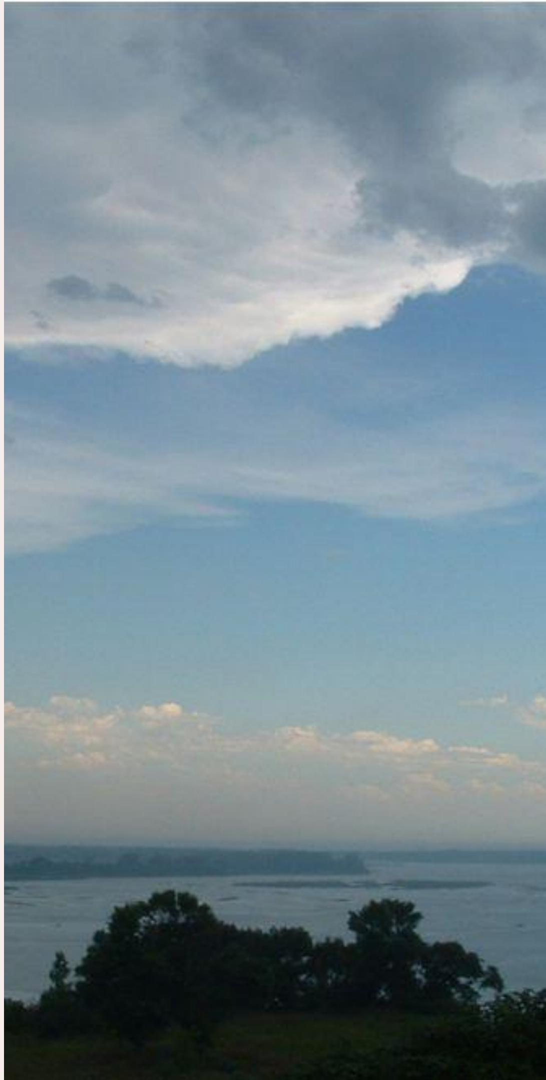
- Pulled all data from January 1, 2020 to September 30, 2025
    - Similar trend in temperature for each year

Train and Test Split

- Test Dataset: September 17, 2025 - September 30, 2025
- Train Dataset: January 1, 2020 - September 16, 2025

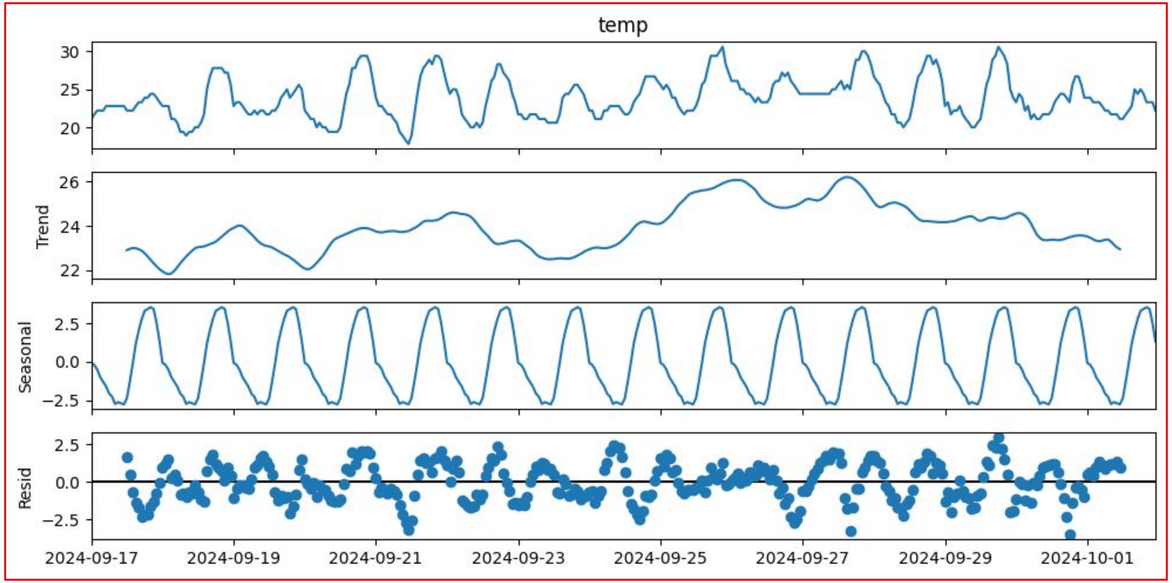
Training data size: **50064 samples**

Testing data size: **336 samples**



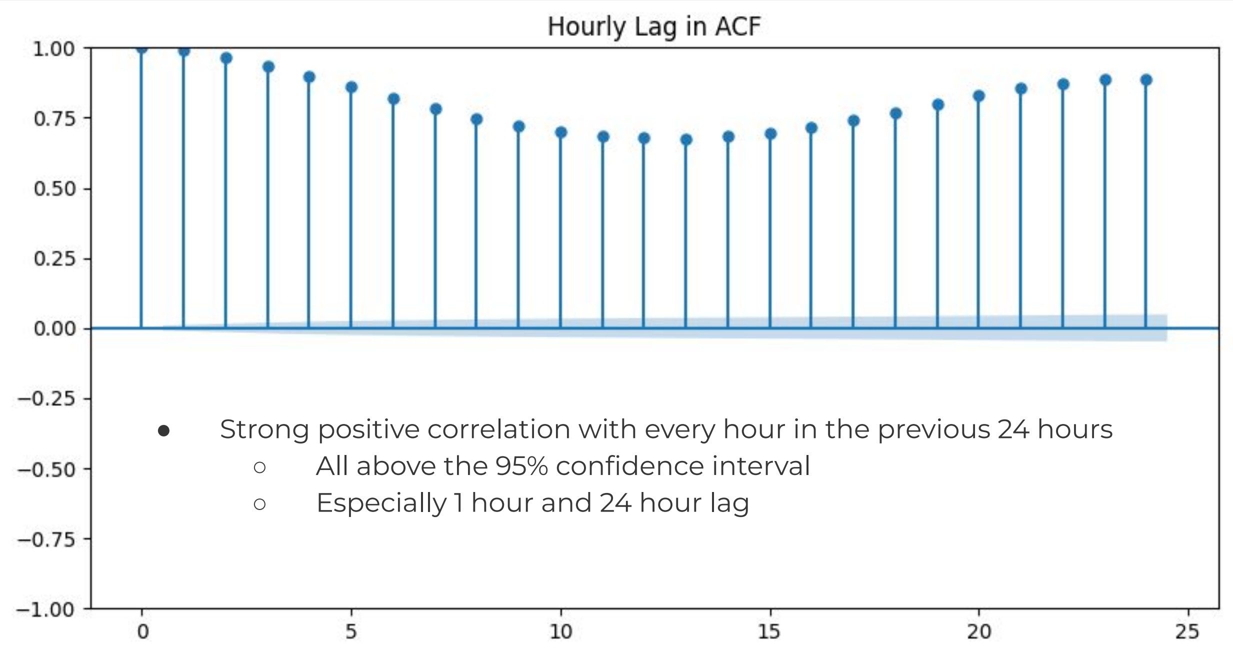
Data Analysis

- No missing data
- Roughly symmetric distribution with slight left skew
- Seasonal Decomposition of temperature during September 17, 2024 - September 30, 2024
    - Non linear trend and daily seasonality



Data Analysis

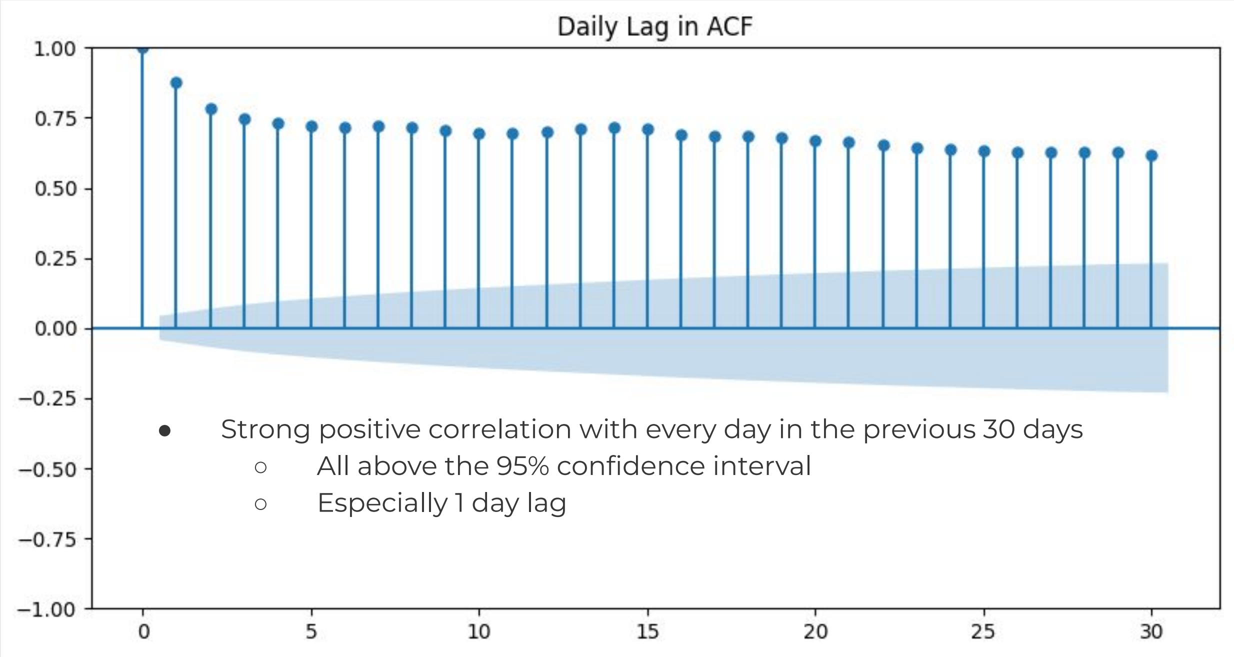
Autocorrelation



- Strong positive correlation with every hour in the previous 24 hours
    - All above the 95% confidence interval
    - Especially 1 hour and 24 hour lag

Data Analysis

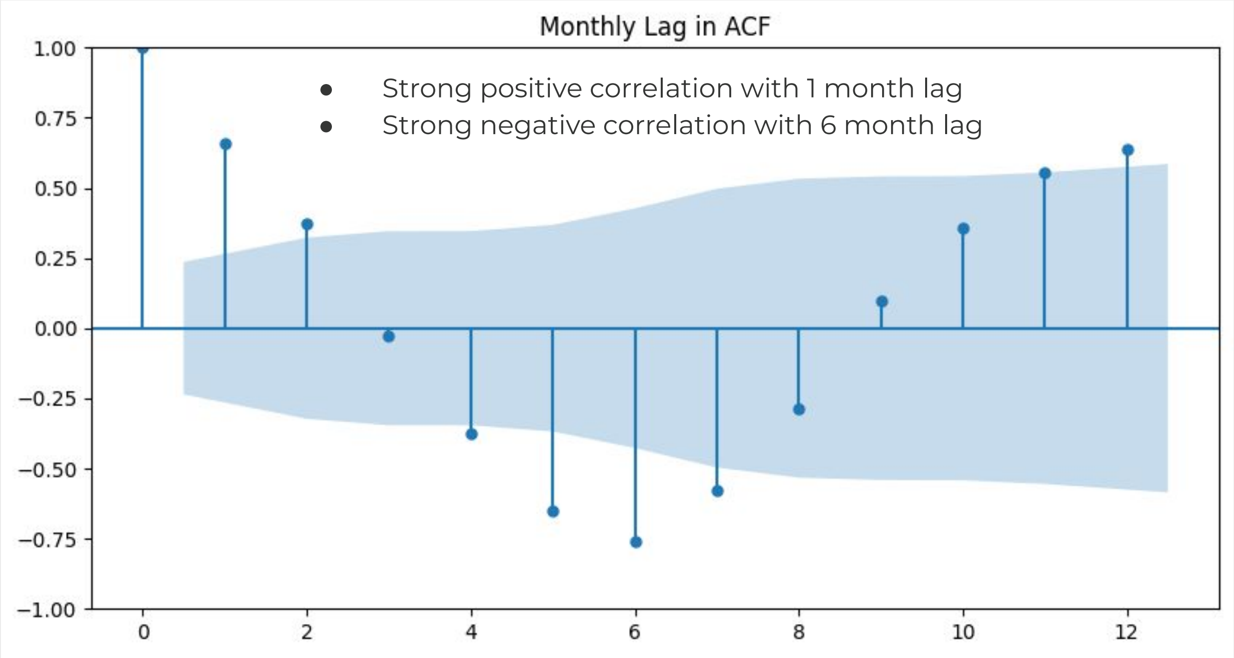
Autocorrelation



- Strong positive correlation with every day in the previous 30 days
  - All above the 95% confidence interval
  - Especially 1 day lag

Data Analysis

Autocorrelation

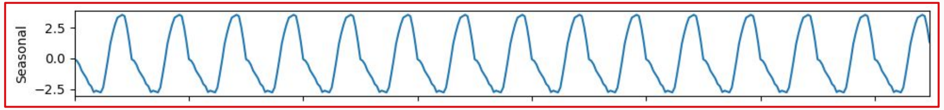


Feature Engineering

Pure Calendar Features

- Year (2020-2025)
- Month (1-12)
- Day (1-31)
- Hour (0-23)
- Day of Year (1-336)
- Day of Week (0-6)

Sine / Cosine Transformation



Cyclical Calendar Features

- captures seasonal cycle

- recognizes consecutive seasons

- hour_sin, hour_cos
  - smooth cycle of daily temperature
  - even between hour 23 and hour 0
- doy_sin, doy_cos
  - smooth cycle of temperature over year
  - even between day 365 and day 1
- month_sin, month_cos
  - smooth cycle of monthly temperature
  - even between month 12 and month 1

Harmonic Calendar Features

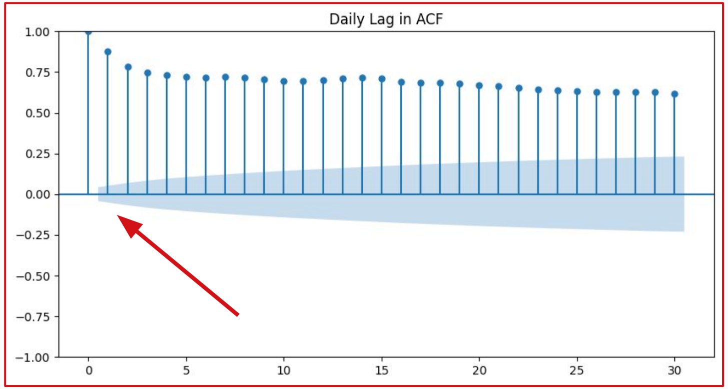
- captures multiple peaks per cycle

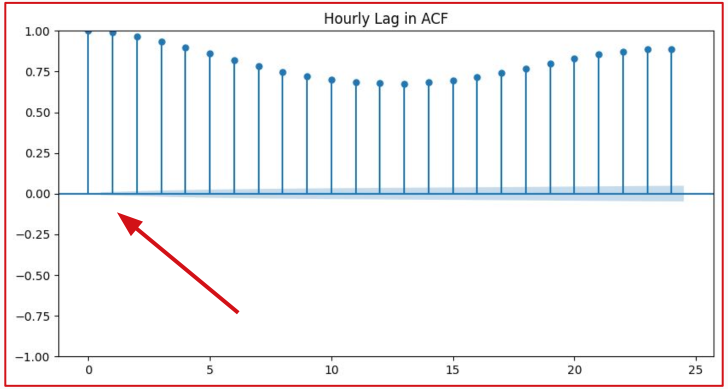
- hour_sin_2, hour_cos_2
  - 2x-daily peaks pattern
- hour_sin_3, hour_cos_3
  - 3 peaks in a day pattern
- doy_sin_2, doy_cos_2
  - 2-annual pattern
- doy_sin_3, doy_cos_3
  - 3 peaks per year pattern

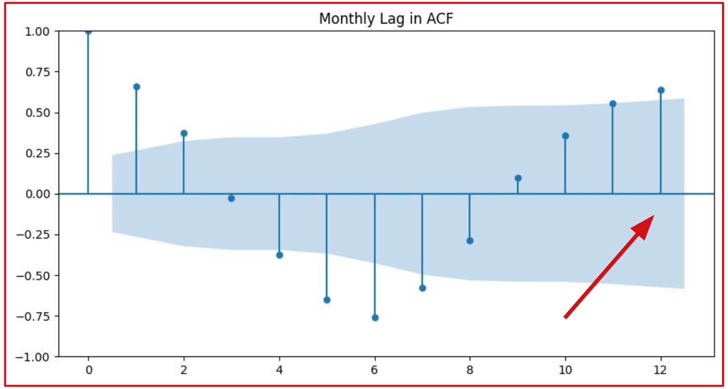
Feature Engineering

Autocorrelation Lags

- previous_hour_temp
  - previous hour's temperature
- previous_day_temp
  - previous day's temperature at same hour
- previous_year_temp
  - previous year's temperature at same month/day/hour

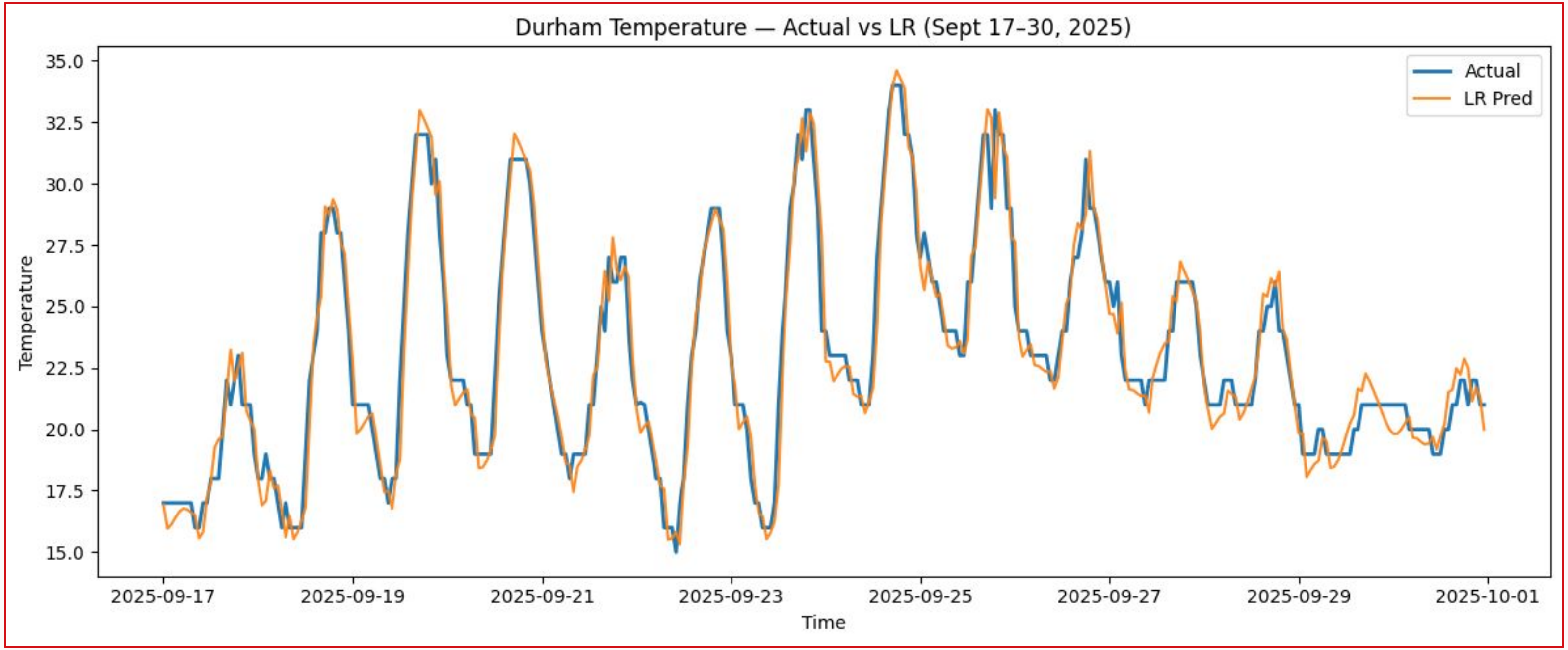




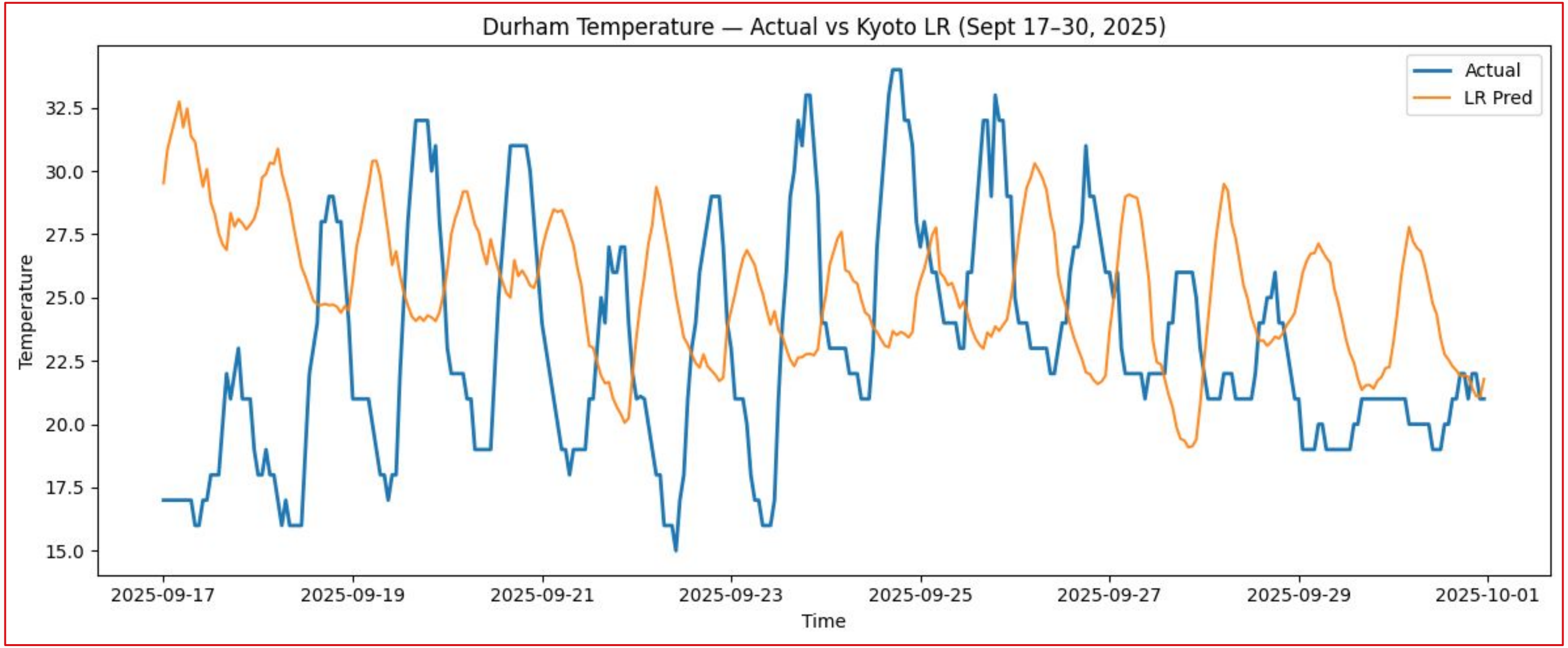


Linear Regression Model

- Most important features: the temperature from the **previous hour** (w=0.972), the **cosine of the hour** (w=-0.821), and the **sine of the hour** (w=-0.791).



Kyoto Model

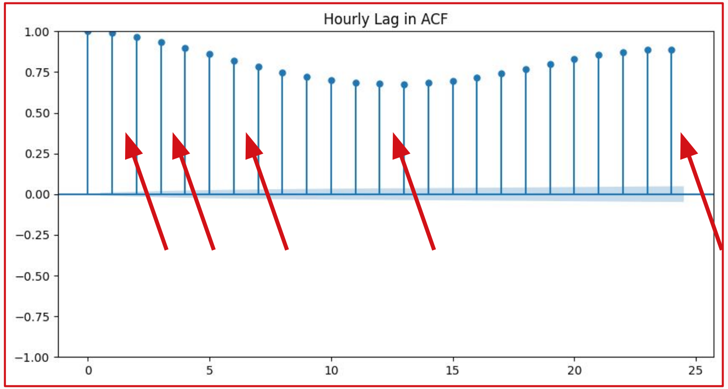


Durham Temperature — Actual vs Kyoto LR (Sept 17–30, 2025)
Actual
LR Pred
Temperature
32.5
30.0
27.5
25.0
22.5
20.0
17.5
15.0
2025-09-17
2025-09-19
2025-09-21
2025-09-23
2025-09-25
2025-09-27
2025-09-29
2025-10-01
Time

Feature Engineering pt2

More Lag Features

- Lag at hours 1, 3, 6, 12, 24, 48

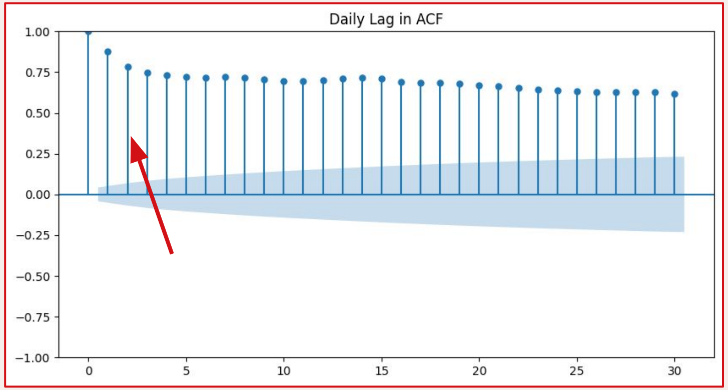


Rolling Statistics

- captures short-term trends

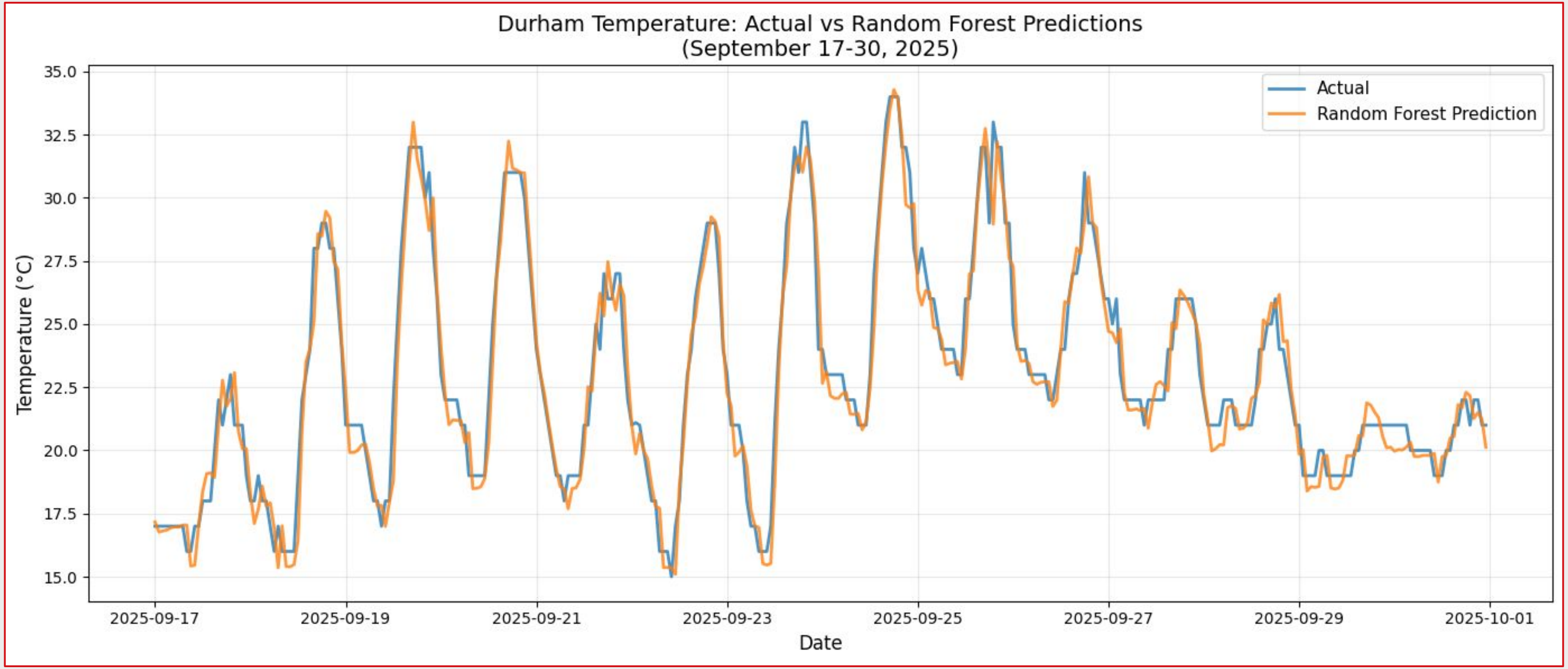
- aggregates temperature over multiple hours instead of one instance

- 24 hour rolling mean and standard deviation
  - weather trend over a day
- 168 hour rolling mean
  - weather trend over the week



Random Forest Model

- Uses multiple decision trees in order to model complex interactions and autoregression
- Hyperparameters: n_estimators = 100, max_depth = 12, min_sample_leaves = 2



Evaluation Approach

How did we evaluate the performance of the models?

1

Checked linear Assumptions

2

Compared with the baseline Linear Regression model

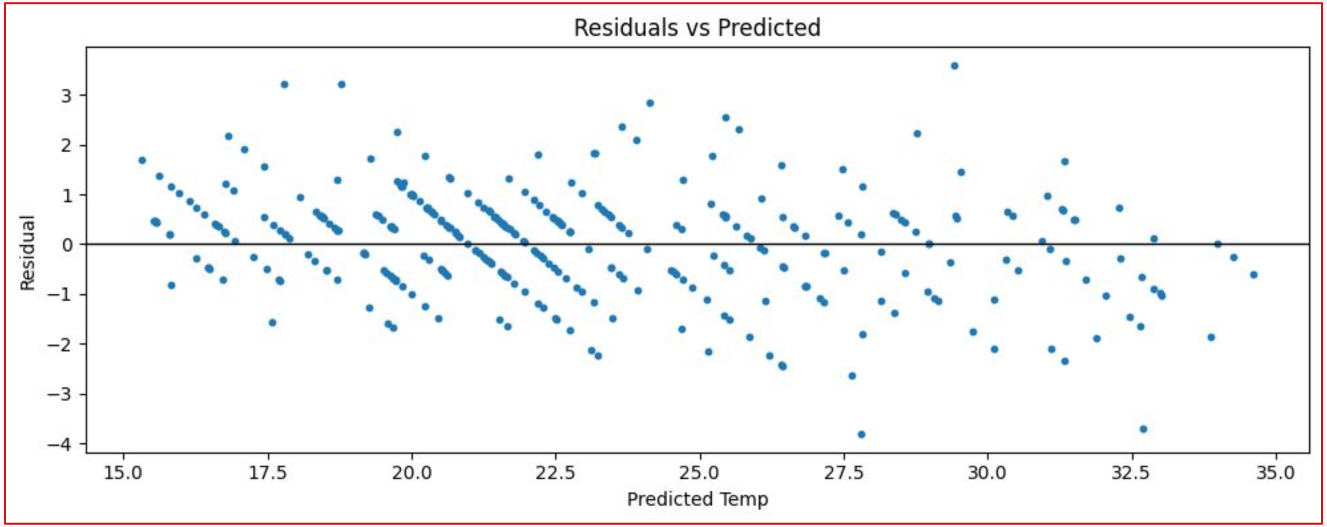
3

Used Time Series Cross Validation to finetune Random Forest hyperparameters

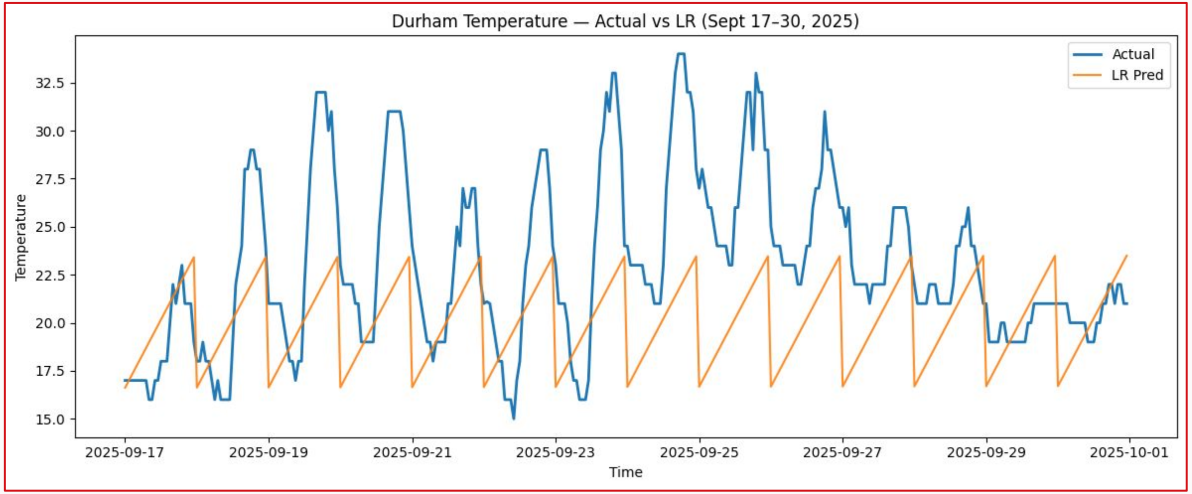
4

Analyzed and compared MSE, MAE, R-squared

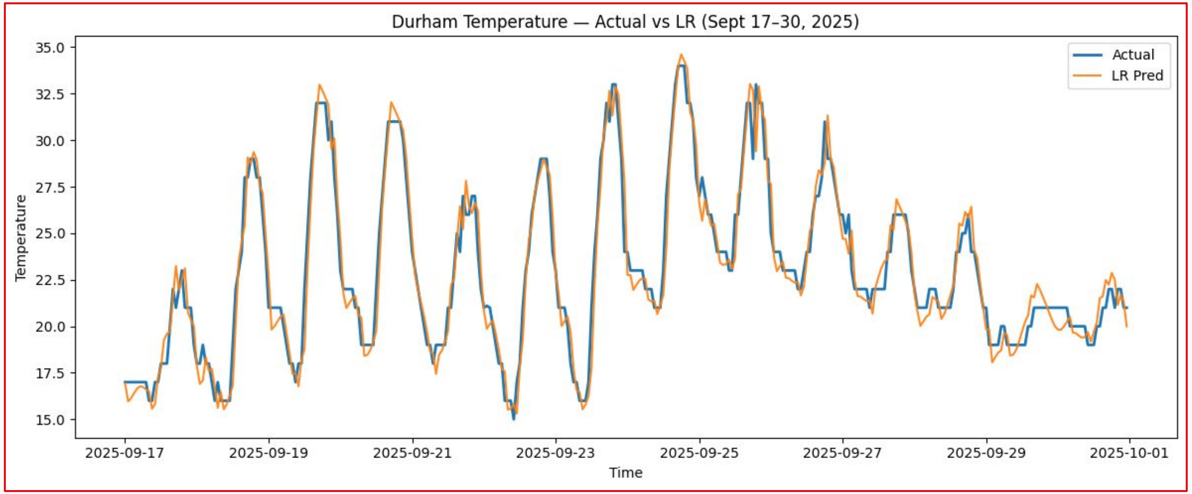
Linear Assumptions



- Linearity: residuals have a pattern
- Homeodascicity: variance of residuals are somewhat equally distributed



Baseline Model



Performance

	Linear Regression	Linear Regression (Kyoto)	Random Forest
MSE	1.11	43.95	0.952
MAE	0.82	5.58	0.756
R^2	0.94	-1.28	0.95

Thank you